Landsat and MODIS imagery for remote sensing classification of cropping practices in western Oregon

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Background

Knowledge of agricultural production practices across the landscape is critical for assessing the impact of farming on ecosystem services and quantifying the effectiveness of conservation programs in protecting the environment. Modern agriculture consists primarily of production of a single annual crop per year, with conservation practices mainly focused on maintaining sufficient residue cover over fall, winter, and spring to protect the soil from excessive erosion during periods when crops are absent or immature. In contrast, agriculture in western Oregon is dominated by perennial crops generally kept in production for multiple years following establishment. Hence, the interface between agriculture and the broader landscape in western Oregon may serve as a useful model for proposed alternative cropping practices across the whole US, including integration of winter cover crops into traditional summer annual production and transformation of annual species into perennials.

A key element of landscape-level analyses of the impact on agriculture on ecosystem services is knowledge of what specific crop management practices are being used on most or all of the fields within individual watersheds or larger drainage basins. Lacking national commitment to simple routine collection of such information in publicly accessible formats during administration of Federal farm programs, it falls on researchers to obtain the ground-truth data needed for training remote sensing classifications of agricultural production practices within his or her geographic areas of interest. Several basic sources exist for ground-truth data: (1) NASS Cropland Data Layers published once every several years for a given state, (2) SSURGO soil maps, and (3) In-house GIS surveys conducted by researchers and their collaborators.

Many platforms exist for generating remotely-sensed data covering on area of interest, each with their own characteristic cost, resolution, spectral bands, return period, and challenges in analysis. Landsat imagery has been widely used in remote-sensing classification projects covering many spatial and temporal scales. Its 25 to 30-m pixels are small enough to accurately identify practices conducted at the scale of traditional agricultural fields without overwhelming the computational abilities of desktop computers and programs such as ERDAS Imagine and ArcGIS. Costs for Landsat images traditionally ran \$450 to \$600 per scene, scenes covered ~55,000 km^2, and the staggered timing between Landsat 5 and 7 passes provided the possibility of new data every 8 days. Regions subject to frequent cloud cover (such as western Oregon) often had less than a dozen usable (i.e., mostly cloud-free) images per year from the two operating Landsat systems, and hardware failures on the satellites have impacted data quality, especially the Landsat 7 Scan Line Corrector (SLC) failure on 31 May 2003. Recent decisions to open the Landsat archives and make all the data free have removed one of the major constraints to their broader use, particularly for lower quality images that were partly cloud covered or affected by SLC failure gaps.

MODIS data contrasts with Landsat in several significant ways. First, its pixel size of 250m poses serious challenges for use with individual agricultural fields, many of which could be covered by a single 6.25 ha pixel, and all of which contain significant border areas for which the field of view (FOV) for a pixel is mixed between the within-field area and neighboring regions outside the specific agricultural field. Although the MODIS orbital repeat cycle is 16 days (similar to Landsat), its swath width of 2300 km generates off-nadir views almost everywhere on earth nearly every day. The 16-day composite product includes a data reliability layer that can be used as a cloud mask along with an NDVI raster. MODIS data are projected in a custom sinusoidal format that presumably centers pixels on some version of the average FOV of the near-daily images that are composited into the product.

Western Oregon crop categories

#	Crop classes from GIS used in remote sensing classification
1	Bare/disturbed ground – other crops (not categories 11-14)
2	Full straw load chop Italian ryegrass
3	Spring plant of new grass seed crops
4	Established perennial ryegrass
5	Established orchardgrass
6	Established tall fescue
7	Mixed-grass pasture
8	Established clover
9	Established mint
10	Hay crop
11	Bare/disturbed ground – Italian ryegrass
12	Bare/disturbed ground – new perennial ryegrass
13	Bare/disturbed ground – new tall fescue
14	Bare/disturbed ground – new clover
15	All wheat
16	All meadowfoam

Classifying partly cloudy images

While cloud-free (and instrument error gap-free) data represents the ideal, only four, three, and two Landsat image acquisition dates were entirely cloud-free and image defect-free in the 2004-05, 2005-06, and 2006-07 grass seed growing seasons in western Oregon. These cloud-free images were supplemented with two partly cloudy Landsat 5 images in each of the first two cropping years and with three partly cloudy Landsat 5 and three partly cloudy and SLC failure gap-afflicted Landsat 7 images in the third year. Cloudy pixels were defined based on visual inspection of the RGB composite image with manual setting of cut-off values for various bands to generate masks with sharp edges of the presumed clouds. Cloud masks from multiple bands were merged to create a single cloudy vs. cloud-free mask which was applied to all seven Landsat bands plus calculated NDVI (Band 4 – 3)/(Band 4 + 3) for a single date. This assured that values were either present or absent from all eight bands at each individual location in an 8-band composite raster dataset. One half of all agricultural fields in each year for each of 16 classes were assigned to the training set, with the other half reserved for test validation. We found ArcGIS image signature creation and maximum likelihood (ML) classification easier to use than the similar processes in ERDAS Imagine as long as composite raster datasets had no more than 20 bands, although results were similar. Only ERDAS Imagine could handle composite rasters of more than 20 bands. ML classification was performed separately for composited raster datasets with common cloud-free areas. ERDAS Imagine was more sensitive than ArcGIS to variability among raster bands in data gaps and format.

In addition to masking out clouds, we corrected a number of other flaws before using image classification procedures on Landsat data. First, image geo-referencing was tested at prominent landmarks (Corvallis Municipal Airport runways and a horse-shoe bend in the Willamette River 13 km NNE of the airport) and image offsets were adjusted to achieve sub-pixel accuracy at the landmarks. In worst case scenarios, unadjusted images were 200 to 300 m out of position. Second, we inspected the NDVI for visually apparent striping across known grass seed fields, and adjusted the digital numbers (DN) in one set of 8-pixel wide alternating stripes up or down to better match DNs in the other stripes. We also encountered several images in which zigzag spatial offsets were apparent at major NS and EW highways, and corrected those errors within separate sets of stripes before merging data back together. Rasters were kept in 8-bit integer format to minimize file size.

Ways to adjust MODIS resolution

Collection 4 MODIS data for calendar years 2004, 2005, and 2006 were obtained from the Global Land Cover Facility in College Park, MD, and clipped to smaller areas of interest (the tri-state PNW or western OR). NDVI and cloud cover rasters were converted from sinusoidal 250m pixel format to 50m NAD83 UTM 10N, taking care to have the 50m pixels closely align within the original 250m pixels. We identified 13, 12, and 15 MODIS 16-day composite NDVI that were entirely cloud-free for our training and test validation set areas, along with three others the first year and two more in each of the next two years that were over 99.7% cloud-free. We acquired Collection 5 MODIS data from LP-DAAC for calendar year 2007, and subjected it to similar steps to those used for the Collection 4 data. The data reliability raster layer within the Collection 5 was not identical to the cloudiness layer in Collection 4, and we considered the two most reliable classes in Collection 5 as matching the single most cloud-free class in Collection 4.

In an attempt synthesize higher resolution data out of the MODIS NDVI, we subjected the 50m converted rasters to 3 by 3 neighborhood averaging. For the 25 new 50m pixels generated from each original 250m pixel, the central 9 pixels had values identical to the original single large pixel, while the other 16 became averages of two, three, or four neighboring pixels. Comparing training and test validation set accuracies for 50m rasters with or without the 3 by 3 neighborhood averaging, there was an average 2.4% increase in accuracy from use of neighborhood averaging on the MODIS data, as well as an increase in Kappa of 0.031. The 50m pixels were resampled to 30m when merged with Landsat data into large multiband datasets (max 89 bands in 2007).

We also tried removing pixels near the outer boundaries of agricultural fields as a means to further improve classification accuracy for MODIS data. This was done by using 3 by 3, 5 by 5, 7 by 7, and 9 by 9 neighborhood averaging of rasters combining training and test validation set ground-truth classes, and removing any pixels not matching their original values. The 3 by 3 neighborhood method removed 26% of all training and test validation pixels, while the 5 by 5, 7 by 7, and 9 by 9 methods removed 47, 61, and 72% of the areas, and in some cases removed entire classes of cropping practices. The 3 by 3 method increased accuracy within the smaller training and validation areas by an average of 4.0%, and even slightly increased accuracy (+0.3%) when tested against the original full-sized ground-truth areas. The 5 by 5 and 7 by 7 methods further increased accuracy within the smaller remaining test areas, but decreased accuracy over the original full-sized areas. The 9 by 9 method failed spectacularly, as did simple removal of all data within 125 m buffers around field edges.

Multi-image classification results

Composite datasets pooled over multiple Landsat dates plus MODIS achieved accuracies as high as 91.5 and 76.0% in training and test validation areas. Merging the best available classifications at each pixel, accuracies of 87.6 and 72.7% existed over entire training and validation areas. Replacing pixels with inconsistent multi-year classifications with fuzzy class two improved validation accuracy to 73.7%. Majority rule reclassification in field polygons increased accuracy to 89.2 and 76.4%.

Classification accuracy 2006-07

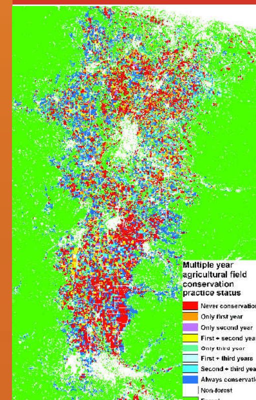
2006-07 Landsat and MODIS images and composite groups	Cloud- and defect-free field area (30m pixels)	Training set accuracy (%)	Training Kappa	Validation accuracy (%)	Validation Kappa
Landsat 16 July 2006	5099313	51.2	0.403	50.1	0.382
Landsat 1 August 2006 [a]	3206395	50.1	0.372	47.2	0.320
Landsat 17 August 2006 [a]	4761149	44.2	0.319	42.6	0.296
Landsat 2 September 2006 [a]	4575739	47.3	0.349	44.0	0.306
Landsat 20 October 2006 [a]	4337255	48.6	0.347	47.1	0.323
Landsat 29 March 2007	5099313	48.1	0.357	45.9	0.326
Landsat 8 May 2007 [a]	4784218	55.6	0.444	52.6	0.417
Landsat 24 May 2007 [a]	4708592	57.7	0.474	55.0	0.436
Landsat 25 June 2007 [a]	4404371	60.3	0.509	57.4	0.466
17 Modis NDVI [b]	5039102	61.9	0.541	52.8	0.428
3 groups pooled fewer Modis [c]	5099250	74.9	0.701	63.8	0.566
3 groups pooled all Modis [c]	5039120	75.5	0.708	63.8	0.567
4 groups pooled (41 bands) [c]	4730368	78.9	0.750	66.5	0.600
5 groups pooled (49 bands) [c]	4403193	80.3	0.765	67.7	0.612
6 groups pooled (57 bands) [c]	3822915	83.8	0.807	69.9	0.638
7 groups pooled (65 bands) [c]	3631621	85.7	0.830	71.4	0.656
8 groups pooled (73 bands) [c]	3294858	86.3	0.837	70.9	0.651
9 groups pooled (81 bands) [c]	2877697	89.5	0.874	74.4	0.689
10 groups pooled (89 bands) [c]	2246360	91.5	0.897	76.0	0.705
final merge [d]	5099250	87.6	0.854	72.7	0.675
replace inconsistent pixels	5036869	87.5	0.852	73.7	0.688
majority rule polygons	-----	82.2	0.796	71.9	0.677
majority rule raster	5020374	89.2	0.872	76.4	0.717

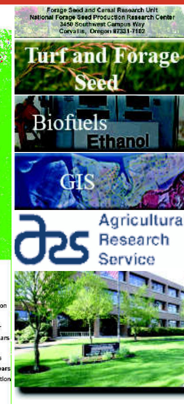
[a] Partial cloud cover on these dates.
[b] Includes 15 MODIS 16-day composite NDVI cloud-free for training and validation set areas plus 2 other with less than 0.3% clouds. Period covered by MODIS data is day 193 of 2006 through day 177 of 2007.
[c] Image signature creation and maximum likelihood classification were conducted for all available cloud-free (and image defect-free) Landsat and Modis raster bands, following which the least cloudy of the remaining images were successively added to the pooled raster collection until all data were included.
[d] Final merge assigned value from maximum likelihood classification of largest number of groups at each pixel.

Results of MODIS adjustments

Year	Ground-truth field edge removal	MODIS resolution enhancement	Evaluation region	Accuracy	Kappa
2004-05	None	None	Full size training	54.6	0.452
2004-05	3 by 3 neighbor	None	Full size training	54.8	0.456
2004-05	5 by 5 neighbor	None	Full size training	54.4	0.452
2004-05	7 by 7 neighbor	None	Full size training	52.7	0.434
2004-05	3 by 3 neighbor	None	Reduced training	59.2	0.503
2004-05	5 by 5 neighbor	None	Reduced training	63.0	0.545
2004-05	7 by 7 neighbor	None	Reduced training	64.7	0.565
2004-05	None	None	Full size training	54.6	0.452
2004-05	None	3X3 averaging	Full size training	57.3	0.486
2004-05	None	None	Full size validation	48.9	0.379
2004-05	None	3X3 averaging	Full size validation	48.9	0.380
2004-05	3 by 3 neighbor	None	Reduced training	59.2	0.503
2004-05	3 by 3 neighbor	3X3 averaging	Reduced training	61.8	0.536
2004-05	3 by 3 neighbor	None	Reduced validation	52.6	0.417
2004-05	3 by 3 neighbor	3X3 averaging	Reduced validation	54.5	0.442
2005-06	None	None	Full size training	52.0	0.411
2005-06	None	3X3 averaging	Full size training	55.2	0.452
2005-06	None	None	Full size validation	48.2	0.362
2005-06	None	3X3 averaging	Full size validation	50.1	0.388
2005-06	3 by 3 neighbor	None	Reduced training	56.2	0.459
2005-06	3 by 3 neighbor	3X3 averaging	Reduced training	59.5	0.501
2005-06	3 by 3 neighbor	None	Reduced validation	51.8	0.402
2005-06	3 by 3 neighbor	3X3 averaging	Reduced validation	54.0	0.431

RS multi-year conservation status





*Remote sensing classes 4-10 of each year viewed as being conserved.

POSTER NUMBER 13